Detection of Non-Invasive Haemoglobin Level using Deep Learning

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ABSTRACT
Haemoglobin is measured via the traditional "fingerstick" test, which entails invasively drawing blood from the body. Traditional laboratory measures are accurate, but they have limitations such as time delays, patient discomfort, biohazard exposure, and a lack of real-time monitoring in critical situations. Researchers are paying close attention to non-invasive haemoglobin assessment since it can assist in identifying polycythemia, anemia, and a range of cardiovascular disorders earlier. This study looks at image-based research using a Deep Convolutional Neural Network for detecting haemoglobin levels. A diverse set of finger images with varying hemoglobin levels was employed to train the model. During testing, the model correctly classifies the haemoglobin level in a realistic condition.

Keywords
Deep Learning, CNN, non-invasive, Haemoglobin detection, DCNN.

1. INTRODUCTION
Haemoglobin is a protein molecule that carries oxygen to our tissues and is found in our blood. Red blood cells keep their form by the amount of haemoglobin they contain[1]. The form and number of red blood cells in a person's blood produce a variety of serious illnesses, such as anaemia and sickle cell. A multitude of medical disorders require the detection of haemoglobin levels for diagnosis and triage.In order to diagnose these disorders, haemoglobin concentration is measured in a clinical setting in an invasive manner[2]. Haemoglobin (Hb or Hgb) level measurement is one of the most commonly requested laboratory tests[3]. The ability to detect haemoglobin levels early on can help in diagnosis. Invasive procedures, despite their high accuracy, offer a

variety of disadvantages for both patients and health care providers. Because intrusive methods need blood samples, this method is not normally recommended for monitoring Hb levels in premature neonates, the elderly, pregnant women, sickle cell, or anaemia patients. The test can take a long time, and the results aren't always available right away. It causes a lag in diagnosis, which has an impact on treatment and result[4]. This technique puts patients' lives at jeopardy, putting them at high risk and increasing future medical costs[5].

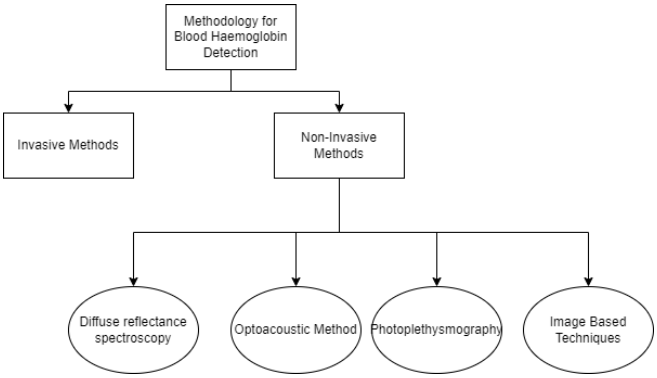

Fig 1: Framework of Deep CNN using RESNET-100

2. LITERATURE SURVEY
[6] shows a comprehensive review on all techniques that exist for blood haemoglobin detection. The diagram below shows the summary for the same.

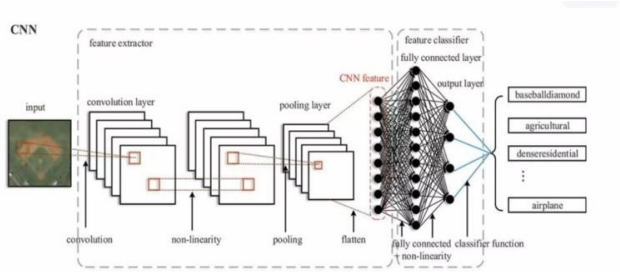

Fig 2 : Methods for Blood Haemoglobin Detection

[7] The authors proposed a non-invasive approach for measuring haemoglobin in this paper. They split the red, green, and blue channels after selecting the area of interest from the collected image. They devised a formula based on the conjunctiva's pixel values, and standard constant values were found by an iterative method to optimize the predicted haemoglobin by comparing the results to known haemoglobin values and repeating the calculation after modifying the constants . They used an 18% photographic standard grey image card to standardize the separated images. The algorithm's efficacy was not tested in patients

with hypoxia or hyperbilirubinemia, or in different light conditions.

In contrast, Collings et al. [8] employ a non-invasive approach for anemia diagnosis. They establish a correlation between the haemoglobin content and the conjunctival erythema index (EI), which is determined from digital images captured under normal lighting conditions. In their method, each image is segmented into its 8-bit red, green, and blue channels, and brightness is adjusted using the mean brightness of the white square on the color calibration card to standardize the conjunctival image capture. Their calculation of EI is based solely on the red and green channels. Despite the effectiveness of their image standardization process in reducing the impact of ambient lighting on EI, it did not completely eliminate this effect. Variations in lighting conditions and lighting intensity still affected the observed relationship between EI and haemoglobin levels.

The authors[9] offer two anaemia diagnosis algorithms. The first algorithm is a two-stage classifier with a thresholding decision technique based on a feature called high hue rate in the first stage and pixel value derivation (PVM) in the second stage, followed by a minimum distance classifier based on Mahalanobis distance. The second algorithm uses 18 features taken from an image of the palpebral conjunctiva. To increase the algorithm's effectiveness, more patient data should be collected to identify better parameters of the suggested technique, such as the HHR threshold. Because the colour distribution of palpebral conjunctiva in this situation is quite similar to that of a non-anemia case, this algorithm cannot handle the anaemia scenario involving severe anger or high blood pressure.

[10] Using a smartphone camera to observe palpebral colour, the authors devise a non-invasive haemoglobin and anaemia testing method. The colour intensity (Red, Green, and Blue) was assessed using Colorgrab software (Loomatix) and compared to the samples' known haemoglobin concentration.

The researchers[11] created a wearable device to capture images of the palpebral conjunctiva, and they identified "distinctly red" regions in the images and calculated results using support vector machines. To improve the device's performance, there must be a method that automatically disqualifies images that are not suitable for analysis.

[12]Diffuse reflectance spectroscopy was employed on the palpebral conjunctiva. The authors discovered that it improved diagnosis over observational research. This leads to advancements in non-invasive haemoglobin detecting technologies.

[13] Diffuse reflectance spectroscopy (DRS) was employed by the researchers to track fluctuations in haemoglobin concentrations caused by surgical blood loss. They used fiber-probe based spectra to determine light diffusion and absorption in tissues.

The researchers[14] propose an approach for predicting hematocrit levels non-invasively. It utilizes a portable spectrophotometer to perform a chemometric examination of the thumbs' visible and near-infrared (Vis–NIR) spectra.

These studies[15 - 16] show that optoacoustic methods can be used to detect haemoglobin in blood circulating in arteries or veins in a non-invasive and real-time manner using optoacoustic signals created by brief light pulses. They discover a very good outcome for in vitro trials, but there were no results available for these in vivo experiments.

This paper[17]presents a non-invasive haemoglobin detection method based on a smartphone. The photos acquired from a person's fingertip were correlated with haemoglobin concentration by the author.

The authors[18]employed LEDs as the source of frequency to create a non-invasive, real-time haemoglobin monitor system based on the photo-plethysmography (PPG) approach. The Hb sensor was clipped to a fingertip, and light was then transmitted through the fingertip.

3. PROBLEM STATEMENT

This research amis to design and develop a system for detection of haemoglobin level using collaboration of deep learning techniques.

Objectives

- To examine and analyze different non-invasive haemoglobin detection methods in a real-time environment.
- To develop an algorithm for detect the haemoglobin level of users based on finger image.
- To develop a Deep Convolutional Neural Network (DCNN) for detection of haemoglobin in real time scenario.
- To explore and validation the accuracy of proposed system with various existing systems.

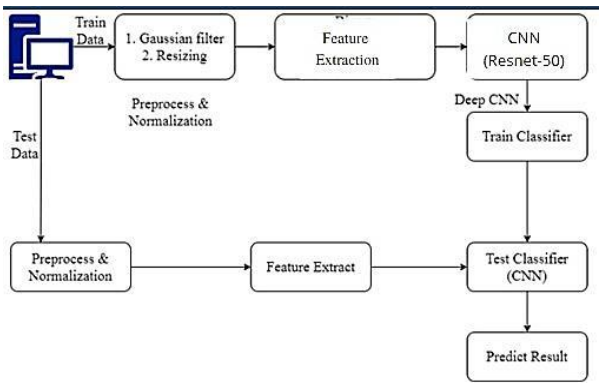

Fig 3 : Proposed System Architecture

3.1 Data Preprocessing And Normalization

Before any analysis can begin, the images of the finger must to be cleaned and standardized. These images may exhibit variations in lighting, size, and noise, which might interfere with the model's performance. First, the images are resized to a common resolution, ensuring uniformity. Any noise present in the images, such as specks or background elements, is removed using image filtering techniques. To standardize the data further, normalization is applied to scale pixel values. This means each pixel's intensity is adjusted to fall within a predefined range (commonly between 0 and 1). Normalization ensures that different image conditions (like brightness) don't skew the model's learning process, allowing it to focus solely on features related to haemoglobin levels.

3.2: Feature Extraction And Selection

At this stage, the goal is to extract significant patterns from the finger images that are indicative of haemoglobin concentration. The deep convolutional neural network (DCNN) automatically detects these patterns by applying various filters in its convolutional layers. Some features may relate to the color intensity of the skin, while others could focus on subtle changes in texture. As the model processes more images, it begins to identify which features are most strongly correlated with haemoglobin levels. The feature extraction process allows the model to isolate these meaningful patterns, while feature selection eliminates any irrelevant data that might confuse the model. This step ensures that only the most predictive aspects of the images are passed on for further processing.

3.3 : Module Training (DCNN)

In the training phase, the DCNN is fed a dataset of finger images along with their known haemoglobin levels. This allows the network to learn how the visual cues in the images map to the actual haemoglobin values. By adjusting its internal weights based on the errors it makes (i.e., when its prediction differs from the known haemoglobin value), the DCNN gradually becomes better at predicting haemoglobin levels. The network uses backpropagation and optimization techniques like gradient descent to minimize its error. Over many iterations (epochs), the model refines its understanding of how the color, texture, and other image features relate to haemoglobin concentration.

3.4 : Module Testing (DCNN)

Once trained, the DCNN is put to the test using new, unseen images of fingers with known haemoglobin values. The model's predictions are then compared to these actual values to assess how well it performs. Metrics like mean squared error (MSE) or mean absolute error (MAE) are used to determine how close the model's predictions are to the real haemoglobin levels. If the model shows high accuracy, it means it has successfully learned to generalize from the training data to new data, making it a useful tool for non-invasive haemoglobin estimation. Should the model underperform, further refinement of the feature selection process or additional training data might be necessary.

3.5: Haemoglobin Report Generation:

Once the model has been trained and tested, the final stage involves generating a haemoglobin level report based on the predictions. For a given input finger image, the DCNN processes the image through its trained layers, extracting relevant features and making a prediction about the haemoglobin level. This predicted value is then used to generate a report, which may include the estimated haemoglobin concentration, whether the levels fall within a healthy range, and any necessary recommendations for further medical evaluation. This report can be presented in a user-friendly format, making it easier for healthcare professionals or users to interpret the results quickly. In a real-time system, this process can be automated, allowing for instant feedback after capturing a finger image.

3.6 DCNN Feature Training And Optimization

- **Input:** Training Dataset (TrainData[]), Activation Functions (activationFunctions[]), Threshold (T).
- **Output:** Extracted Features (Feature_set[]) for the trained module

Step 1: Use the activation function (e.g., ReLU) on the input data (data[]) with a specified epoch size.

Step 2: Extract features from the input data using:

Features.pkl ← ExtractFeatures(data[])

Step 3: Optimize the extracted features and assign them to the feature set:

Feature_set[] ← Optimize(Features.pkl)

Step 4: Return the Feature_set [].

3.2 DCNN Feature Matching and Evaluation

- **Input:** Testing Dataset (TestData[]), Training Dataset (TrainData[]), Threshold (T).
- **Output:** ResultSet <class_name, Similarity_Weight> for all items where Similarity_Weight exceeds T.

Step 1: During training, the weights of each filter associated with the convolutional layers are trained. During inference, the sample is passed through the trained network to create:

testFeature(k) = Σ (featureSet[Z[i], Z[n]] ← TestData)
from m=1 to n

Step 2: Create a feature vector from the extracted testFeature(m):

Extracted_FeatureSet_X[t … n] = n(t) ← testFeature(k)

Step 3: For each training instance, apply:

trainFeature(l) = Σ (featureSet[Z[i], Z[n]] ← TrainData) from m=1 to n

Step 4: Generate a new feature vector from trainFeature(m):

Extracted_FeatureSet_Y[t … n] = Σ (TrainFeature(l)) from t to n

Step 5: Evaluate each test record against the entire training dataset in the dense layer:

weight = calcSim(FeatureSet_X || Σ FeatureSet_Y)

Step 6: Return Weight.

It will show the level or count of haemoglobin of specific user using DCNN.

4. EXPERIMENTAL RESULTS AND ANALYSIS

This study examines the performance of a Deep Convolutional Neural Network (DCNN) in predicting hemoglobin levels from finger images. The evaluation of the model's effectiveness is based on several key metrics, including accuracy, mean absolute error (MAE), and its ability to generalize to unseen test data. Experiments were conducted using a dataset of finger images, with hemoglobin levels validated against clinical measurements. This comprehensive analysis provides insights into the model's performance and its potential applicability in real-world scenarios

4.1 Haemoglobin Detection Accuracy

The DCNN model was trained using a subset of the dataset and tested on new, unseen finger images. The table below summarizes the key results of the experiment, including accuracy rates for different haemoglobin ranges, average prediction error, and the number of correctly predicted cases across both training and testing datasets.

Table 1. Accuracy at different range

Haemoglobin Range (g/dL)	Accuracy (%)	Mean Absolute Error (g/dL)	Correct Predictions (Test Data)	Correct Predictions (Training Data)
< 10	92.5%	0.85	180	210
10 - 12	90.1%	0.95	190	220
12 - 14	88.7%	1.10	170	200
> 14	85.2%	1.25	160	190

4.2 Analysis

From the table, it is evident that the model shows a high level of accuracy in predicting haemoglobin levels, especially in the lower ranges (<10 g/dL), where the accuracy reaches 92.5%. However, the performance slightly declines for higher haemoglobin ranges, with an accuracy of 85.2% for values greater than 14 g/dL. This is likely due to the model encountering fewer training examples for high haemoglobin values, leading to a slight increase in the mean absolute error. Overall, the model performed effectively in estimating haemoglobin levels across a variety of ranges, demonstrating its capability as a non-invasive method for haemoglobin detection.

5. RESULTS AND DISCUSSION

The evaluation of Deep Convolutional Neural Networks (DCNN) systems was carried out using a setup with an Intel i7 CPU running at 2.7 GHz and 16 GB of RAM, chosen to ensure sufficient processing power and memory for the intensive computations required. The latest iteration of the system, called "RESET," was used, specifically versions 32, 50, 101, and 152, to examine performance across different implementations. Key performance metrics included execution time, memory usage, network overhead, and energy consumption. Execution time was measured through various stages like data processing, model inference, and training operations. Memory usage was tracked during model loading, data handling, and peak performance stages, while network overhead was assessed in terms of data transfer rates, latency, and bandwidth where applicable. Energy consumption was also a critical metric, analyzed by measuring the power draw and calculating efficiency based on energy used relative to performance. These factors provided a detailed understanding of how well the different versions of the "RESET" system handle DCNN tasks, giving a clear picture of their effectiveness and efficiency for complex neural network applications.

Table 2. Data processing time with various deep method

Data Sample	*CaffeNet*	*GoogleNet*	*AlexNet*	*VGGNet*	*RESNET*
100	73.2	73.5	74.2	73.98	79.23
200	76.2	77.2	75.7	74.2	81.6
500	75.2	79.5	77.8	76.6	82.3
1000	77.1	78.9	76.2	77.0	83.2

The above Table 2 describes an data processing time for all deep models using TensorFlow for different data size.

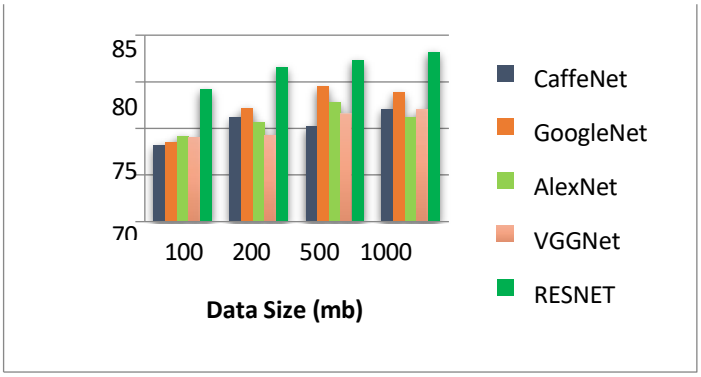

Fig 4: Framework of Deep CNN using RESNET-100

The above Fig 4 also describes a visual interpretation of Table I that provides how accuracy should be increased when data load has enlarged. It sometimes depends on current trained modules and heterogeneous data modules.

6. CONCLUSION

In medical research, a significant challenge arises when developing classifier models due to data imbalance, where certain classes have insufficient data. This imbalance can adversely affect the accuracy and reliability of prediction models. Addressing this issue requires the implementation of effective strategies and methodologies. This study focuses on leveraging non-invasive techniques to detect haemoglobin levels from real-time input images. By employing a Deep Convolutional Neural Network (DCNN), the goal is to enhance the precision of these detections. The proposed system utilizes advanced algorithms to analyze image data, producing estimated measurements with high accuracy. Future improvements could involve incorporating synthetic data generation techniques to address class imbalance, refining model architectures to enhance performance, and integrating additional features for more robust predictions. Additionally, using diverse datasets and real-time image processing could further improve the system's reliability and adaptability in practical medical settings. This approach not only advances the field of medical imaging but also provides valuable insights for developing more effective diagnostic tools.

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